Building and Environment 150 (2019) 206–218

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Development of the data-driven thermal satisfaction prediction model as a function of human physiological responses in a built environment

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ARTICLE INFO

Keywords:
Occupant behavior
Thermal satisfaction estimation
Physiological response
Skin temperature
Heart rate

ABSTRACT

The purpose of this study is to investigate and determine the relationship between occupants' thermal satisfaction and physiological responses in an office environment, and to estimate their thermal satisfaction level via human physiological signals. This study adapted the heart rate and seven local body skin temperatures as physiological signals, as well as human factors (gender, age, BMI), to determine establish a thermal satisfaction prediction model by combining human factors and physiological signals. The results revealed significant correlations between overall thermal satisfaction levels and local body skin temperatures, as well as heart rates. The heart rates showed a negative correlation with overall thermal satisfaction, and the skin temperature of the forehead, arm, wrist (back and front), chest, and belly also revealed a significant correlation with the thermal satisfaction levels of the study participants. This study also determined the order and priority of local skin temperatures (as well as gender and BMI) by their impact on thermal satisfaction. Considering all human physiological factors and practical application of the results, the local skin temperatures of the forehead, wrist (back), and gender demonstrated 88.52% accuracy for estimating thermal satisfaction, which provided significant validation for practical use of this procedure.

1. Introduction

In modern daily life, people spend 87% of their time indoors [1], so architects and engineers have tried to achieve indoor environmental satisfaction for building users, while minimizing building energy consumption. Thermal comfort is defined as 'the condition of mind that expresses satisfaction with the thermal environment' [2]. Many modern buildings use mechanical systems to maintain an acceptable indoor thermal environment based on an existing thermal comfort model, such as ASHRAE's Predictive Mean Vote (PMV) [3]. These thermal comfort models are based on pre-defined equations or empirically verified recommendations, which rely on aggregated thermal perceptions of an occupant group [4].

However, these models rarely consider individual preferences or physiological factors (such as age and gender), that have been considered to be significant factors for thermal sensation [5–9]. Therefore, the thermal dissatisfaction of office occupants in the United States appeared higher than 60%, even though indoor temperatures were maintained within a prescribed comfort range [10–12]. In addition, this uniform control of indoor thermal environment did not just fail to provide a comfortable thermal environment for study participants, but it also consumed a large amount of energy [13]. Moon revealed that PMV model-based control systems provided too much heating or cooling due to their technical features, which resulted in over-performance of the building's systems [14].

To overcome these issues, recent studies have approached micro-scale control systems, considering individual controls [15–20]. Goyal et al. [21] investigated multiple algorithms and performance through simulation studies. In the result, they showed that the occupancy-based control algorithm achieved significant energy savings over a conventional temperature control algorithm. Other researchers also reported significant HVAC energy savings, from 4% to 75%, through individual thermal environmental control settings [15–20,22,23]. Gupta et al. [24] investigated an occupant feedback-based temperature control system, and indicated the possibility of an optimum temperature setting, while minimizing a building's energy consumption as well as maintaining thermal comfort through a mechanical system. Murakami [16] studied the on-line control system by using input from occupants, and showed a 20% HVAC energy savings over that of a conventional thermostat setting. Vesely and Zeiler [25] also investigated personalized thermal environmental conditioning to optimize thermal comfort and energy efficiency. They revealed that the proposed system

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https://doi.org/10.1016/j.buildenv.2019.01.007
Received 30 September 2018; Received in revised form 24 December 2018; Accepted 5 January 2019
Available online 11 January 2019

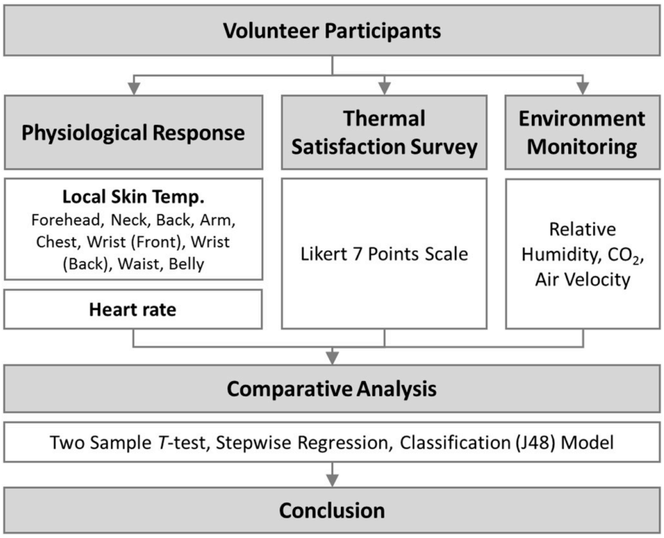

Fig. 1. Research flow including experimental procedures.

Table 1
Demographic information (Number of participants).

	Underweight	Normal Weight	Over weight	Sub-total
Male	3	5	2	10
Female	2	4	–	6
Total	5	9	2	16

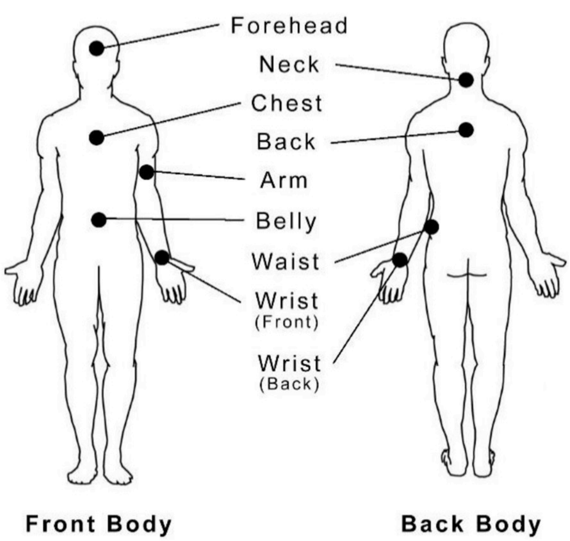

Fig. 2. Local body spots for measurement.

prevented over-cooling or excessive heating, and saved up to 60% in energy consumption for the HVAC system, while successfully maintained an acceptable thermal comfort level for occupants.

However, because it may not be practical for building occupants to

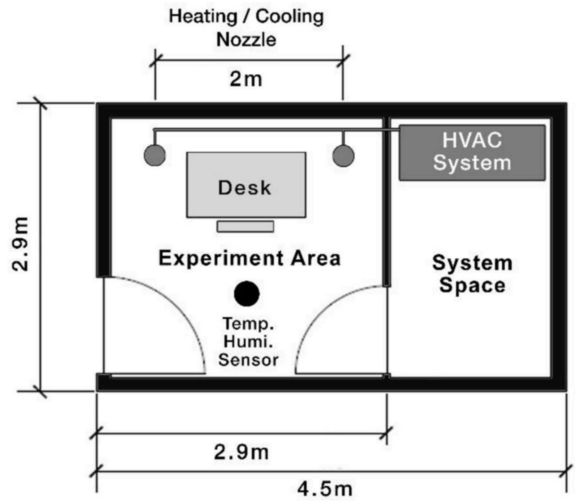

Fig. 3. Experiment chamber floor plan.

input their thermal information or satisfaction into the system every time, some researchers have investigated the thermal comfort prediction model that is based on the physiological signals of an occupant [26–30]. These prediction models rely on the principle that the physiological signals could be correlated with thermal comfort/sensations [29,31]. However, it is difficult to assess an occupant's thermal comfort in real-time, based on human physiological signals, due to the subjective nature of thermal comfort and various relevant human factors. On the contrary, advanced modern sensors and analysis algorithms, such as machine-learning, provide various possibilities, and recent researchers have approached the problem from this perspective.

Zhou et al. [32] studied three different thermal sensation models to predict an individual's thermal sensation, via monitoring skin temperatures, and suggested the most effective one. Feng et al. revealed the impact of air supply on thermal comfort by using a personal nozzle system based on skin temperature monitoring, as well as a thermal sensation survey [33]. They reported the most effective local body spots for cooling, and suggested the ideal position of the nozzles. Chaudhuri et al. [34] also investigated a thermal comfort prediction model, based on normalized skin temperature. They presented an estimation model of the thermal state with 87% accuracy via local skin temperature and its gradient. Wu et al. [35] studied local body skin temperatures, focusing on the upper extremities to assess thermal comfort in office buildings. The results revealed that upper extremity skin temperatures satisfactorily predicted thermal sensations as well as assessing thermal comfort. Additionally, Choi and Yeom [36] investigated local body skin temperature as a function of whole body thermal sensation prediction model. This study adopted seven local body skin temperatures, and revealed the best combination of local body segments for predicting a whole body thermal sensation.

Although these recent studies considered human physiological signals to predict an individual's thermal comfort, much research focused on a thermal sensation prediction model, and a very limited number of studies investigated the direct relationship between physiological responses and thermal satisfaction. Also, many studies used correlation

Table 2
Thermal satisfaction questionnaire using the Likert 7-Point Scale.

-3	−2	−1	0	1	2	3
Very Dissatisfied	Dissatisfied	A little Dissatisfied	Neutral	A little Satisfied	Satisfied	Very Satisfied

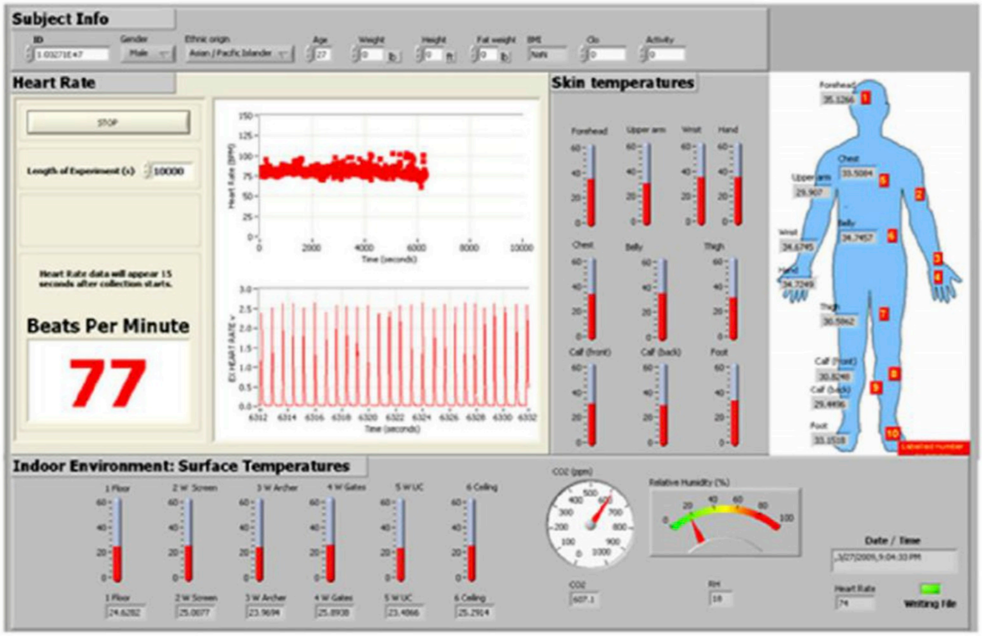

Fig. 4. Monitoring interface of DAQ system.

Table 3
Sensor specifications.

Sensor	Model	Specification
Air temperature	LM35DT	Accuracy: ± 0.5 °C (at 25 °C), Resolution: 0.01 °C, Sensing range: -55 °C ~ 150 °C
Air velocity	Testo 405-V2	Accuracy: ± 0.1 m/s + 5%, Resolution: 0.01 m/s
CO_2	Telarire 6004	Accuracy: ± 40 ppm
Radiant temperature	OS-542	Accuracy: ± 2 °C, Resolution: 0.1 °C
Relative humidity	HIH-4000-003	Accuracy: 3.5%, Resolution: 0.5%
Heart rate	HER-BTA	Transmission frequency: 5 kHz ± 10%
Skin temperature	SBS-BTA	Accuracy: ± 0.5 °C, Resolution: 0.03 °C
Data acquisition board 1	Sensor DAQ	Resolution: 13 bit, Sampling rate: 10 kS/s
Data acquisition board 2	NI-DAQ 6008	Resolution: 12 bit, Sampling rate: 10 kS/s

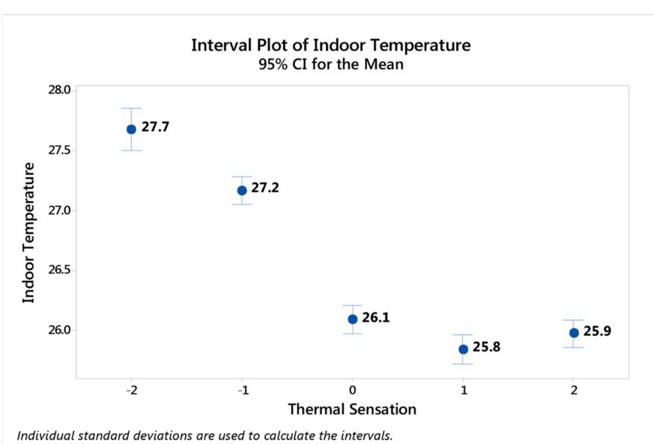

Fig. 5. Interval plot of the indoor temperature by thermal satisfaction level.

analysis to consider a single local body area, rather than a combination of multiple areas. Furthermore, some studies did not consider human factors (such as gender, age, or body mass index (BMI)) that have been reported to have a significant impact on thermal satisfaction.

Therefore, the purpose of this study is to investigate the relationship between an individual's thermal satisfaction level and physiological responses in an office environment, and to accurately estimate the thermal satisfaction of each user via human physiological signals. This study adapted the heart rate and seven local body skin temperatures as a physiological signal, as well as human factors (e.g., gender, age, BMI), to develop a thermal satisfaction prediction model based on a combination of human factors and physiological signals.

2. Methodology

2.1. Experimental procedure

A series of human subject experiments were conducted to collect local body skin temperatures and heart rates. The experiments were approved by the IRB (Institutional Review Board: UP-16-00104) of the University of Southern California (USC), and a consent form was signed and collected from each participant before the experiment began. The overall research flow is illustrated in Fig. 1.

The volunteers were mostly students at USC, with a total of 18 recruited to participate (7 females and 11 males). After an initial analysis, two datasets were excluded from the results due to sensor damages, and the remaining 16 datasets were processed for analysis in this study.

The average age of the participants was 24.6 (Standard Deviation (SD): 2.64), and the average BMI was 20.59 (SD: 3.50). Each

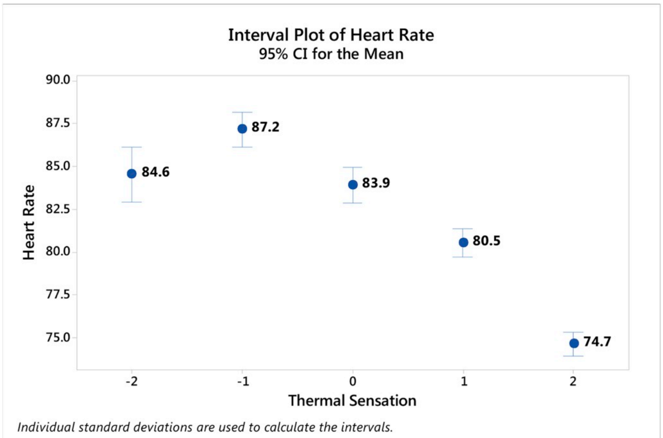

Fig. 6. Interval plot of the heart rate by thermal satisfaction level (95% CI for the mean).

participant's physical condition was normal without any specific health issues. Each participant was asked to wear simple clothes for Clo level 0.55 or 0.59 (a long sleeve T-shirt: 0.25, long pants: 0.25, socks: 0.02, panties: 0.03, bra: 0.04). Basic physical information of each participant (such as age, weight, and height) was surveyed, and the body mass index (BMI) was calculated. Basic demographic information is summarized in Table 1.

To stabilize his or her physiological condition before the experiment started, a participant remained for 30 min in a waiting area where the temperature was maintained at 24 °C by the central HVAC system of the building. Then, the participant moved into the environmental chamber for testing, where the initial temperature (controlled by the independent HVAC system) started at 20 °C, and a thermal satisfaction survey was administered, and skin temperature, heart rate, and indoor environmental data were collected. The indoor temperature was increased from 20 °C to 30 °C. The temperature change rate was 1 °C per 10 min and the thermal satisfaction survey interval was synchronized with it. This interval of temperature change, that could be perceived by a participant, was based on previous human subject research [7,12,37]. Seven local body areas, from which local body skin temperatures were to be collected, were chosen based on the 16 most frequently selected thermoregulation models [37,38]. The local body areas selected were the forehead, neck (back of the neck), back (upper part), chest, waist, arm (upper arm), and belly (illustrated in Fig. 2).

During the experiment, a participant sat on a chair by a desk, while moderate music played. A general office chair, with polyester mesh support (back and bottom), was used to minimize any possible insulation effect of the chair on a participant's thermal satisfaction. A participant stayed in the experiment room for 100 min, while the location and posture of the participant were maintained as uniform as possible. Once the experiment started, participants were asked to mark their thermal satisfaction on a check list every 10 min. The Likert 7-points scale was used for the thermal satisfaction check list (Table 2), which was based on the ASHRAE PMV survey [3]. The indoor environmental data, local body skin temperatures, and heart rates were constantly recorded every 10 s.

2.2. Experiment chamber

The experiment was conducted in the experiment chamber at USC, which consisted of a 2.9 m × 2.9 m experiment area and 2.9 m × 1.5 m system space (Fig. 3). An independent HVAC system was used to control the air supply, and the air velocity was maintained lower than 0.2 m/s, based on the ASHRAE recommendation [3]. A desk and chair were located in the center of the experiment area, and data collection equipment was also installed. The indoor temperatures of the experiment area were monitored at four different heights (0.1 m, 0.6 m, 1.1 m and 1.7 m), and the result,1.1 m, was used for an analysis, that considered the height of the participant's head/neck in a sitting position. The relative humidity (RH) and CO_2 density were monitored to check any irregularity in the experiment area, based on ASHRAE standard 62.1 [39]. During the experiment, the RH was maintained at 35%, and the CO_2 density was between 700 and 900 ppm. Air nozzles were located at each side of the desk on the floor, and were controlled to minimize the air velocity around the desk and chair. During the experiment, the measured air velocity was 0.1 ± 0.05 m/s at the height of the floor level, 0.6 m, 1.2 m, and 1.6 m. This was an acceptable range based on ASHRAE standard 55 (maximum 0.2 m/s) [3].

2.3. Equipment

Labview-based Data Acquisition (DAQ) system was installed and used to collect physiological data on participants, as well as indoor environmental data (Fig. 4). The DAQ system was installed in a desktop computer, and recorded the indoor temperature, RH, CO_2 density, air velocity, radiant temperatures, heart rates and local body skin temperatures. Specifications for each monitoring sensor are summarized in Table 3.

2.4. Data analysis

The collected data was analyzed using multiple statistical methods, such as the two-sample T-test, Anova, correlation analysis, and stepwise regression analysis. Minitab and Microsoft Excel were the main tools used for data analysis, and the statistical analysis were conducted at a 95% significant level. Additionally, WEKA (data-mining software) was adopted to generate a decision tree model (J48) and to determine the accuracy of estimates.

2.4.1. WEKA [40]

WEKA is an open source data-mining software, that was developed by the machine learning research group at the University of Waikato in New Zealand. This program includes collections of machine-learning algorithms for data mining tasks, such as data pre-processing, classification, regression, clustering, association rules, and visualization.

2.4.2. J48 decision tree model

The distribution of data can be easily understood with a decision

Table 4
Descriptive statistics of the skin temperatures.

	Forehead	Arm	Wrist (Back)	Wrist (Front)	Chest	Belly	Waist	Back	Neck
Mean	35.646	33.919	33.108	33.275	35.051	34.426	34.890	34.722	34.712
SD	1.424	1.138	2.299	2.322	0.949	1.562	1.578	1.717	1.173
Max	37.181	36.290	37.033	38.853	38.853	36.207	36.885	36.306	36.468
Min	29.115	30.113	27.322	29.610	29.610	26.544	22.636	26.762	27.289

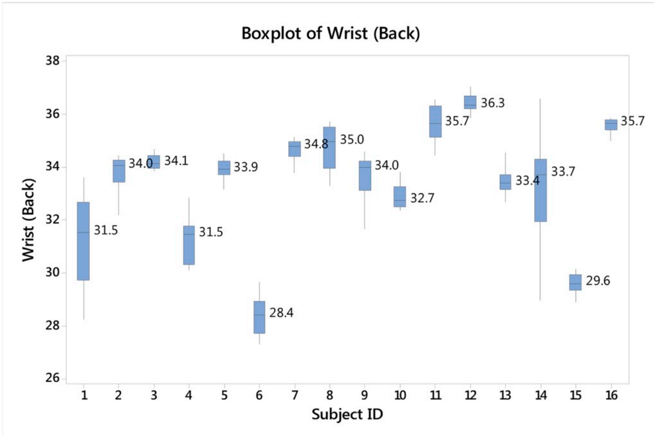

Fig. 7. Box plot of wrist (back) skin temperatures by individual participant.

tree algorithm [41]. A decision tree algorithm generates principles to predict a variable target. The J48 decision tree is the implementation of the algorithm ID3 (Iterative Dichotomiser 3), which was developed by the WEKA project team. The objective of the J48 algorithm is to normalize a decision tree model until it reaches the flexibility and accuracy as an equilibrium [12].

2.4.3. Stepwise regression

Stepwise regression can be applied to build a model by fitting regression models in which the choice of predictive variables is determined by automatic procedures [42]. The process of stepwise regression systematically adds the most significant variable, or removes the least significant one, in each step.

3. Results

3.1. Comparison of physiological responses and thermal satisfaction

Fig. 5 illustrates a box plot of the indoor temperature at each thermal satisfaction level. After an initial analysis, the data at thermal satisfaction level −3 (very dissatisfied) and 3 (very satisfied) were too small in number to be statistically significant; therefore those were excluded from the analyses for this study. The average indoor temperature decreases from the thermal satisfaction level −2 to 1, and the average value did not show any significant differences in the thermal satisfaction levels of 0, 1, and 2 (Fig. 5). However, it is clear that thermal satisfaction levels were prone to increase as indoor temperatures decreased. A correlation analysis between indoor temperature and thermal satisfaction level also showed a statistically significant negative correlation (Pearson R: -0.369, $p < 0.001$).

This study focuses on two human physiological signals, those from the heart rate and the local body skin temperature, that respond to surrounding ambient temperature changes. Fig. 6 illustrates the interval plot of the heart rate by overall thermal satisfaction level. It is also clear that the heart rate decreased as the overall thermal satisfaction level increased from level −1 to 2, although the heart rate at thermal satisfaction level −2 was a bit lower than the one at level −1. The Spearman R value for heart rate and overall thermal satisfaction level appeared at −0.323, with a significant p-value ($p < 0.001$). Therefore, it is safe to say that the overall thermal satisfaction level is negatively correlated with the heart rate.

Each local body spot is a different size and varing sensitivity that exchanges heat between the human body and ambient air. Since these local body spots are affected by the surrounding ambient air temperature, this study analyzed the overall thermal satisfaction level as a function of each individual local body area. Table 4 summarizes descriptive statistics of aggregated skin temperatures at the nine local body spots, that were monitored during the experiment. The average skin temperature of each local body spot ranged from 33 °C to 36 °C, while the indoor temperature changed from 20 °C to 30 °C. The forehead skin temperature was relatively higher than that of the rest of the body parts, while the skin temperatures of the arm and both wrists (back & front) were lower than the others. Based on the standard deviation (SD), the chest showed the most stable skin temperature variation, while both back and front wrists showed relatively significant large temperature variations.

Fig. 7 illustrates the box plot of the skin temperature of every participant's wrist (back), with the median value (horizontal line in each box) as a sample. Each vertical line and box indicate a quartile of the distributed data. It is clear that each participant generated various skin temperature levels, even though all of them were exposed to the same indoor temperature range. Other local body spots of each participant also showed similar temperature variations, without any specific pattern or tendency.

Table 5 summarizes similar results to those illustrated in Fig. 7 and Table 4, which represent the correlation between local skin temperatures and overall thermal satisfaction level. This reveals that most local body spots (except the waist, back, and neck) have a negative correlation with the overall thermal satisfaction level. Among the physiological responses, the heart rate and local skin temperatures of the belly and arm showed strong correlation with thermal satisfaction, respectively, while the forehead, chest, waist, and neck showed relatively weak correlation. Fig. 8 illustrates the interval plots of the local skin temperature distribution at each thermal satisfaction level, which showed that the overall thermal satisfaction level increased when the local skin temperature decreased. As illustrated, the arm, wrist (back and front), and belly showed a relatively clear declining pattern, while the thermal satisfaction levels of the chest, waist, back, and neck increased. Also, the local skin temperature variations of the wrist (back), wrist (front), and the belly were within 2 °C, respectively, which was significantly larger than that of the other local body areas.

3.2. Comparison of physiological responses and thermal satisfaction by gender

Various studies have described the influence of gender differences on thermal perceptions [43,44]; the monitoring results of this study also verified that there are significant differences in the thermal satisfaction and physiological responses of males and females in the same thermal environment. Table 6 shows that the average thermal satisfaction level of females is significantly higher than that of males, and

Table 5
Correlation analysis of local skin temperatures and thermal satisfaction.

	Fore head	Arm	Wrist (Back)	Wrist (Front)	Chest	Belly	Waist	Back	Neck
Spearman	−0.172	−0.259	−0.165	−0.186	−0.130	−0.334	0.047	0.098	0.065
P-value	$P < 0.001$	$P < 0.001$	$P < 0.001$	$P < 0.001$	$P < 0.001$	$P < 0.001$	0.012	$P < 0.001$	0.001

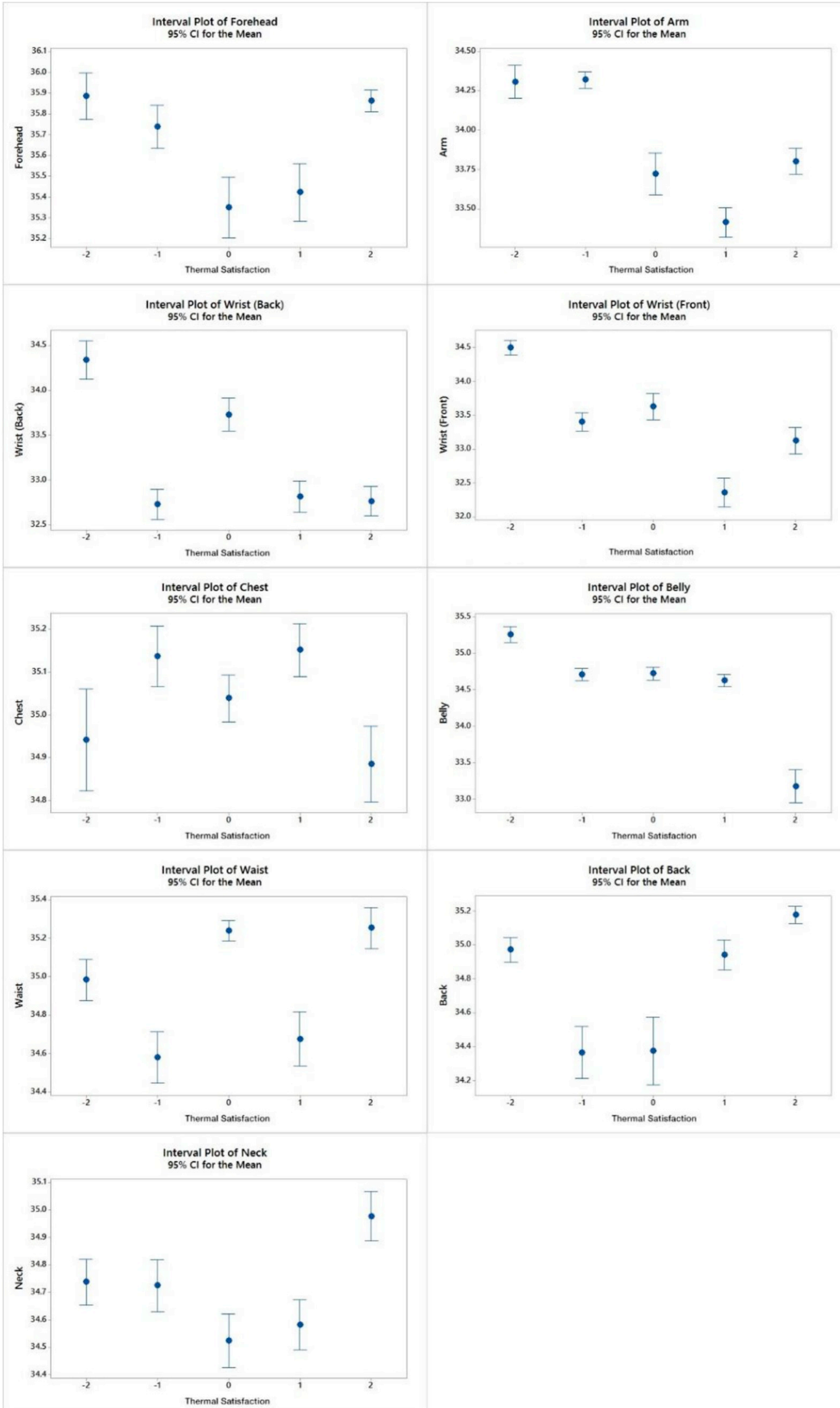

Fig. 8. Interval plot of the local skin temperatures by thermal satisfaction levels (95% CI for the mean).

Table 6
Descriptive analysis and T-test results of thermal satisfaction difference by gender.

	Gender	Mean	SD	T[a]	Df[b]	p[c]
Thermal Satisfaction	Female	0.7668	1.1761	24.24	2486	P < 0.001
	Male	−0.3383	1.2277			
Heart Rate	Female	74.893	8.758	−28.57	2481	P < 0.001
	Male	86.697	11.968			

[a] t-value in T-test.
[b] Degree of freedom.
[c] p-value (calculated probability).

Table 7
T-test results of the heart rate differences by gender at each thermal satisfaction level.

		−2	−1	0	1	2
Mean	Female	89.6	75.5	82.35	74.90	71.08
	Male	84.1	89.8	84.6	87.67	82.51
Δ Mean (Female − male)		5.48	−14.30	−2.287	−12.769	−11.430
P-value		0.047	P < 0.001	0.013	P < 0.001	P < 0.001

the heart rate was also clearly different in that the average for males was higher than that for females. The variations in the thermal satisfaction levels of the male group and the female group were not significantly different, while the average heart rates of the females were more stable than those of the males.

Table 7 demonstrates the heart rate difference, by gender, at each thermal satisfaction level. It shows that there is an overall difference in the thermal satisfaction perceptions of males and those of females. The heart rates of the female group decreased consistently while the thermal satisfaction level was getting higher, but the heart rate of the male group did not show any significant pattern. It was also clear that the heart rates of the male group were generally higher than those of the female group at every thermal satisfaction level, except −2, with a significant p-value. Additionally, the correlation analysis between the heart rate and thermal satisfaction level showed that the Pearson R was −0.378 and the Spearman R value was −0.380 for the female group ($p < 0.001$), respectively, and −0.073 (Pearson R) and −0.048 (Spearman R) for the male group ($p < 0.005$), respectively. This demonstrated that the correlation between the heart rate and thermal satisfaction level of the females was stronger than those of the males.

The local skin temperatures also showed a correlation between the gender groups. Table 8 summarizes the correlation analysis results between the local skin temperature and thermal satisfaction, by gender difference. In the male group, every local skin temperature was negatively correlated with the thermal satisfaction level ($p < 0.01$), while the female group showed negative correlation at five local body areas and positive correlation at four other areas. Also, the arm and back skin temperatures in the female group were not significantly correlated with the thermal satisfaction levels ($p > 0.05$). It is also interesting that the female group had a stronger correlation with the thermal satisfaction levels than the male group when the results were significant, except for the wrist (front).

Fig. 9 (See also Appendix A) illustrates the local skin temperature difference, by gender, at each thermal satisfaction level. In general, the forehead, wrist (back), wrist (front), and neck showed consistent temperature differences between the male group and the female group, and the thermal satisfaction level at these local body spots increased when the skin temperature decreased. The local skin temperatures of the male group were higher than those of the female group at the forehead, chest, back, and neck, while the female group showed higher local skin temperatures than the male group at the wrist (back), wrist (front), and belly. The arm and waist did not show a clear pattern of difference.

3.3. Comparison of physiological responses and thermal satisfaction by BMI

The Body Mass Index (BMI) has been used as a significant physiological factor for thermal sensation [45,46]. The World Health Organization (WHO) classifies BMI in four levels– underweight (less than 18.5), normal weight (18.5–24.9), overweight (25–29.9), and obese (over 30). In this study, two participants were overweight, nine were normal, and five were underweight. Considering statistical significance and comparative analysis, the participants were divided into two groups; high BMI group (eight participants, BMI > 20) and low BMI group (eight participants, BMI < =20). The initial analysis results demonstrated clear differences in the BMI group. In Table 9, the aggregated thermal satisfaction level appeared higher in the low BMI group, than in the high BMI group, with a significant p-value, while the heart rates of the high BMI group were higher than those of the low BMI group. A correlation analysis of the aggregated data also showed significant differences by BMI group. The correlation analysis results between the heart rate and thermal satisfaction level in the high BMI group were −0.070 (Spearman, $p < 0.05$) and −0.099 (Pearson, $p < 0.001$), while the low BMI group showed −0.442 (Spearman, $p < 0.001$) and −0.435 (Pearson, $p < 0.001$). This demonstrated that the heart rates and overall thermal satisfaction levels were more correlated in the low BMI group than in the high BMI group.

The heart rate differences by gender at each thermal satisfaction level are demonstrated in Table 10. It is clear that the heart rate difference between the high and low BMI groups increased as the satisfaction level or dissatisfaction level increased. The high BMI group showed higher heart rates than the low BMI group did at satisfaction levels −1, 1, and 2, while the low BMI group had higher heart rates at thermal satisfaction levels −1 and 1. Therefore, heart rate differences by BMI group are significant at every thermal satisfaction level, even though it does not show a consistent pattern.

The results of an analysis of the correlation between local skin temperatures and thermal satisfaction are shown in Table 11. In general, the high BMI group showed more significant correlation than did the low BMI group, based on the p-value of each local body spot. In the high BMI group, the wrist (back) and chest showed a relatively higher

Table 8
Comparison of correlation analysis results for local skin temperatures and thermal satisfaction by gender difference.

		Fore head	Arm	Wrist (Back)	Wrist (Front)	Chest	Belly	Waist	Back	Neck
Female	Spearman	−0.328	−0.059	0.305	0.217	−0.368	−0.341	0.205	0.004	−0.294
	P-value	P < 0.001	0.054	P < 0.001	P < 0.001	P < 0.001	P < 0.001	P < 0.001	0.893	P < 0.001
Male	Spearman	−0.303	−0.230	−0.236	−0.251	−0.198	−0.205	−0.171	−0.066	−0.191
	P-value	P < 0.001	P < 0.001	P < 0.001	P < 0.001	P < 0.001	P < 0.001	P < 0.001	0.006	P < 0.001

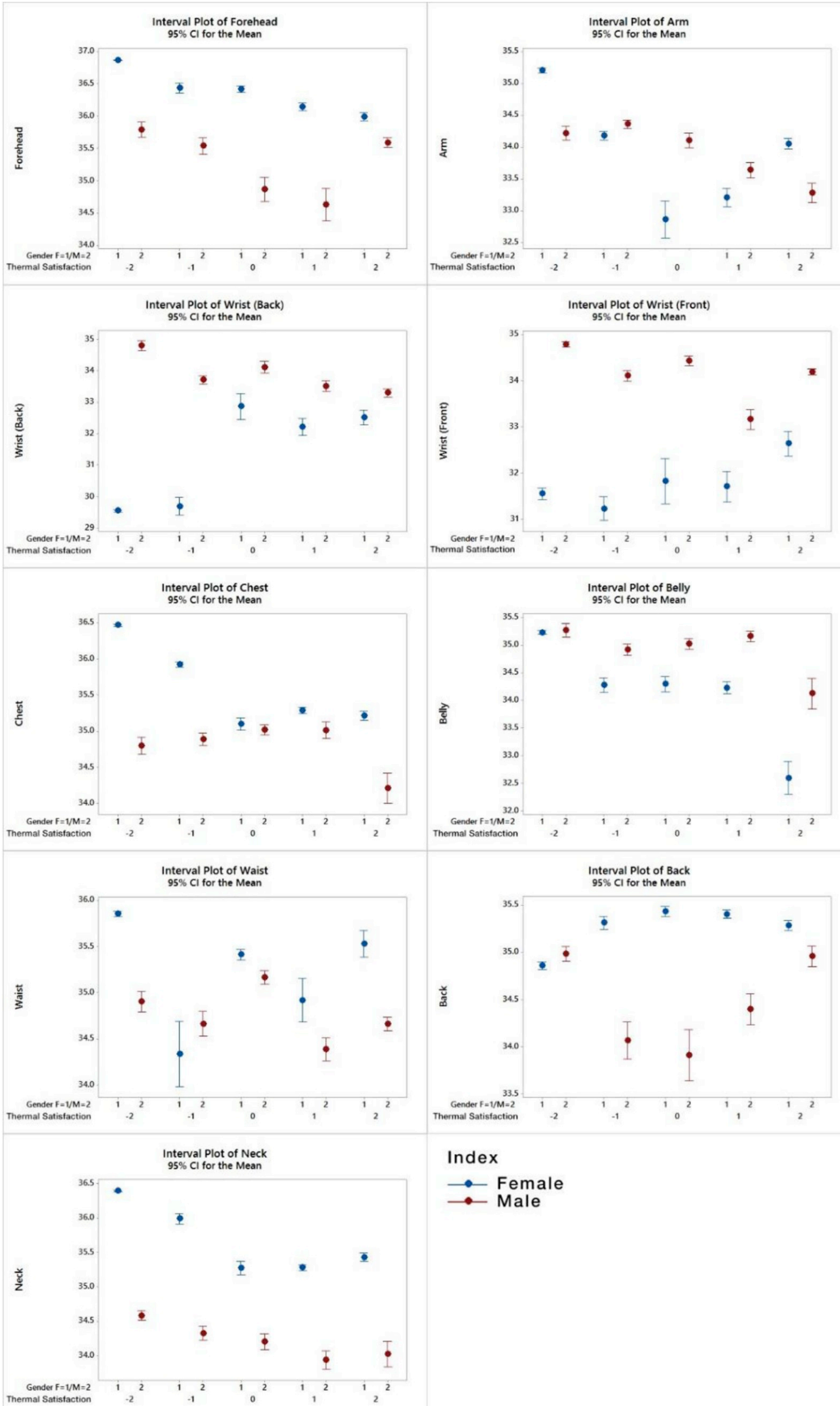

Fig. 9. Interval plot of local skin temperatures by thermal satisfaction level and gender (95% CI for the mean).

Table 9
Descriptive analysis and T-test results of thermal satisfaction differences by BMI.

	BMI	Mean	SD	T[a]	Df[b]	p[c]
Thermal satisfaction	High	−0.3421	1.2715	17.68	2840	P < 0.001
	Low	0.4865	1.2427			
Heart Rate	High	85.804	11.876	−15.92	2519	P < 0.001
	Low	78.397	11.507			

[a] t-value in T-test.
[b] Degree of freedom.
[c] p-value (calculated probability).

Table 10
T-test results of heart rate differences by gender at each thermal satisfaction level.

		−2	−1	0	1	2
Mean	High BMI	81.9	91.4	82.4	85.0	82.51
	Low BMI	100.1	79.9	85.7	78.59	71.08
Δ Mean (High – Low)		−18.15	11.52	−3.37	6.41	−10.31
P-value		P < 0.001	P < 0.001	0.002	P < 0.001	P < 0.001

correlation value than the other local body spots did, while the belly was the highest in the low BMI group. Between the two groups, the high BMI group showed higher correlation than the low BMI group did at the wrist (back), wrist (front), chest, and back, and the low BMI group had relatively stronger correlation than the high BMI group did at the forehead, arm, belly, waist, and neck.

Fig. 10 (See also Appendix B) demonstrate the local skin temperature differences by BMI group at each thermal satisfaction level. It is interesting that both wrists (back and front) showed significantly higher local skin temperatures in the high BMI group than the low BMI group did, while the other local skin temperatures generally showed the opposite results, with consideration of a p-value. The overall thermal satisfaction level generally increased when the local skin temperature was decreasing, except for the waist and back.

4. Discussion

As described in the “3. Results” chapter, the heart rates and local skin temperatures showed diverse results, depending on the local body areas as well as human factors (such as gender and BMI) involved. Through a series of analyses, this study verified some patterns from these physiological responses, which showed a potential for predicting individual thermal satisfaction levels based on selected skin temperatures and heart rate, as well as human factors. Therefore, an in-depth analysis was conducted and described in this chapter to quantify the contributions and priorities of the selected local skin temperatures, heart rate, and human factors on overall thermal satisfaction levels.

4.1. Stepwise regression analysis

Table 12 demonstrates results of the stepwise analysis of the heart rate and local skin temperatures on the overall thermal satisfaction level. Among the physiological responses, the heart rate had the most significant influence on thermal satisfaction (R-sq: 21.16%), and the arm was the second of all, but the first among local skin temperatures. The heart rate and arm were validated for 30.23% on the thermal satisfaction estimation, and the back and forehead also showed higher accountability than the other local body areas did. A combination of all variables showed 52.00% in the accountability of the overall thermal satisfaction.

Similarly, this study conducted an additional stepwise analysis, by gender and BMI group; a summarized R-sq is shown in Table 13. Overall, the analysis results by gender group or BMI group demonstrated a higher R-sq value than the general results did, which verified the significant influence of the human factor on thermal satisfaction. The cumulative results for the high BMI group showed the highest R-sq value of all (70.00%), while the female group demonstrated the lowest accountability among the human factors (64.17%). The priority of the physiological responses varied by the human factor. The heart rate appeared three times for the highest accountability in all participants, in the female group, and in the low BMI group, while the arm, waist, and chest generally showed relatively high validity. All of the participating group (without the human factor) demonstrated the lowest accountability of all (52%); thus, it was clear that the human factor should be included in a thermal satisfaction prediction model. Additionally, it is safe to say that the heart rate, arm, chest, and waist have relatively high accountability for thermal satisfaction prediction.

4.2. Thermal satisfaction prediction model

In the stepwise regression analysis, accountability for the thermal satisfaction prediction was 52–70%, depending on each group. The thermal satisfaction survey data is a discrete number with an interval (7 point scale), while physical data (heart rate and local skin temperatures) are continuous type. These different characteristics in data can be a reason for the relatively low accountability in Tables 12 and 13. Therefore, this study also used J48 algorithm to generate a classification model that accepts thermal satisfaction results as a nominal data. All attributes of physiological signals (heart rate and local skin temperatures), as well as human factors (gender and BMI group), were included in this analysis. The accuracy was estimated by 10-fold cross validation, and the results are demonstrated in Table 14 (See also Appendix C).

Generally, the local skin temperatures demonstrated higher accuracy than the human factors did. The accuracy of every local skin temperature appeared higher than 40%, while all human factors showed lower accuracy than all of the skin temperatures did. Among the skin temperatures, the forehead exhibited the highest accuracy as a single attribute, and the wrist (back) was second. Every human factor showed significantly lower accuracy than local skin temperatures did, which was around 35%. Additionally, combining these attributes significantly increased the accuracy. Among numerous combinations of

Table 11
Correlation analysis of the local skin temperature and thermal satisfaction (Spearman Rho).

		Fore head	Arm	Wrist (Back)	Wrist (Front)	Chest	Belly	Waist	Back	Neck
High BMI	Spearman	−0.174	−0.189	−0.290	−0.198	−0.221	−0.006	−0.090	0.059	−0.127
	P-value	P < 0.001	P < 0.001	P < 0.001	P < 0.001	P < 0.001	0.835*	0.001	0.028	P < 0.001
Low BMI	Spearman	−0.222	−0.306	0.062	−0.040	−0.090	−0.570	0.104	0.035	0.176
	P-value	P < 0.001	P < 0.001	0.017	0.120*	0.001	P < 0.001	P < 0.001	0.172*	P < 0.001

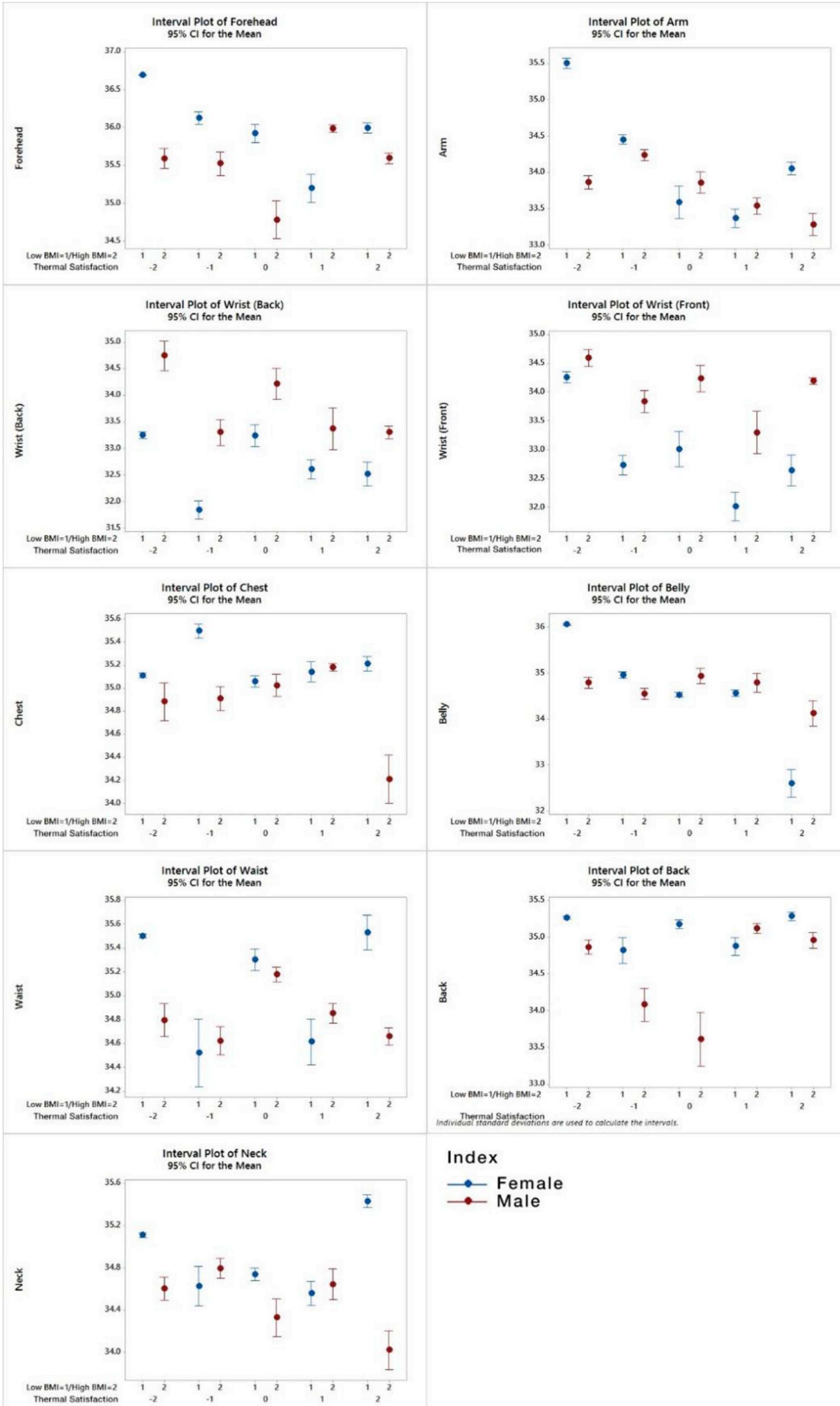

Fig. 10. Interval plot of local skin temperatures by thermal satisfaction level and BMI group (95% CI for the mean).

Table 12
Results of stepwise analysis of physiological responses on thermal satisfaction.

	Step 1		Step 2		Step 3		Step 4		Step 5		Step 6		Step 7		Step 8	
	Coef	p.	Coef	p.	Coef	p.	Coef	p.	Coef	p.	Coef	p.	Coef	p.	Coef	p.
Heart rate	−0.051	p < 0.001	−0.045	p < 0.001	−0.367	p < 0.001	−0.024	p < 0.001	−0.021	p < 0.001	−0.012	p < 0.001	−0.011	p < 0.001	−0.009	p < 0.001
Arm			−0.442	p < 0.001	−0.500	p < 0.001	−0.430	p < 0.001	−0.515	p < 0.001	−0.550	p < 0.001	−0.565	p < 0.001	−0.596	p < 0.001
Waist					0.223	p < 0.001	0.400	p < 0.001	0.563	p < 0.001	0.571	p < 0.001	0.548	p < 0.001	0.547	p < 0.001
Forehead							−0.678	p < 0.001	−1.290	p < 0.001	−1.190	p < 0.001	−1.200	p < 0.001	−1.264	p < 0.001
Back									0.912	p < 0.001	0.981	p < 0.001	0.878	p < 0.001	0.846	p < 0.001
Belly											−0.171	p < 0.001	−0.185	p < 0.001	−0.178	p < 0.001
Chest													0.136	p < 0.001	0.099	0.004
Neck															0.120	0.014
R-sq		21.16		30.23		33.42		39.90		48.47		51.28		51.83		52.00
ΔR-sq				9.07		3.19		6.48		8.57		2.81		0.55		0.17

two attributes, a combination of the forehead and wrist (back) skin temperatures (the first and second highest single attribute) showed the highest accuracy at 83.37%. When the three highest attributes were combined, the forehead, wrist (back), and back, the accuracy increased to 91.36%. Multiple attributes were also combined. The increment of accuracy increased to 95% when five attributes were combined, but the accuracy started to decrease when six were combined, so a combination of five attributes was considered to be the maximum number.

Additionally, it is interesting to see that the human factors showed low influence on the overall accuracy in this analysis, although a significant influence was demonstrated in the previous stepwise analysis. This may be because the stepwise regression model was based on statistical results, while 10-cross validation focused on the generalization of the prediction model. Also, the number of participants may not be large enough to generate a significant variation that is statistically stronger. Among the human factors, gender showed the largest influence on the accuracy of the thermal satisfaction prediction. Even though the influence of the human factors was small, gender and BMI had significant contributions to the thermal satisfaction prediction when it was combined with selected skin temperatures. Gender does not require other measurement tools, and too many attributes can interfere with the data.

Considering these factors, as well as practical application, a prediction model was established for this study (Appendix D), which adopted the forehead, wrist (back), and gender as key factors. It was based on a classifier model (J48 algorithm), and the estimation was verified using the 10-cross validation process, which is common in the data informatics area. The classification model in Appendix D estimates an occupant's thermal comfort level as a function of selected physiological responses. As shown in Appendix D, gender was the most influential variable in this thermal satisfaction estimation model, and its thermal satisfaction predictions were 88.52% accurate.

5. Conclusion

This study investigated the relationship between an individual's thermal satisfaction and human physiological responses to estimates an overall thermal satisfaction level as a function of human physiological signals (such as local body skin temperature and heart rate, as well as gender and BMI) via an experiment using 16 participants in the environment chamber.

This study revealed significant correlations between overall thermal satisfaction levels and local body skin temperatures, as well as the heart rates. The heart rate showed a negative correlation with overall thermal satisfaction, while skin temperatures of the forehead, arm, wrist (back and front), chest, and belly also revealed a significant correlation with the study participants' thermal satisfaction levels. In addition, this study also determined the order and priority of local skin temperatures (as well as gender and BMI) by their impact on thermal satisfaction perceptions. Considering all human physiological factors and practical application of the results, the local skin temperatures of the forehead, wrist (back), and gender demonstrated an 88.52% accuracy rate for thermal satisfaction estimations, which provides significant validation for their practical use.

The results of this study can be implemented in a building's indoor thermal environmental control system, which requires user-centric, micro-scale, and individual control these days. The technical evidence of this study has high potential as support for a thermal environmental system controlled by an individual using a wearable monitoring device (such as a smart band or smart watch). It will contribute to providing better indoor environmental quality while the number of participants was 16, in this study, which demonstrated a statistically significant result. However, a larger number of sample sizes will increase the validity and accuracy of those results, especially with regard to the differences posed by gender and BMI. Additionally, other human factors (such as age and ethnicity) should be considered for a future study as

Table 13
Stepwise analysis results (Cumulative R-sq) considering human factors.

All participants		Female		Male		High BMI		Low BMI	
Heart rate	21.16	Heart rate	30.80	Arm	21.30	Forehead	31.28	Heart Rate	29.62
Arm	30.23	Chest	39.93	Waist	36.47	Chest	52.73	Belly	39.61
Waist	33.42	Waist	45.92	Neck	51.07	Waist	56.63	Arm	48.03
Forehead	39.90	Back	48.94	Wrist (Back)	54.93	Back	61.18	Neck	53.41
Back	48.47	Wrist (Back)	54.67	Forehead	56.94	Wrist (Front)	64.90	Back	58.18
Belly	51.28	Forehead	58.75	Back	64.80	Arm	69.45	Wrist (Back)	64.12
Chest	51.83	Belly	60.26	Chest	66.71	Belly	69.92	Chest	65.16
Neck	52	Arm	62.63	Hear rate	67.32	Heart Rate	70.00	Waist	66.06
		Neck	63.45	Wrist (Front)	67.40			Wrist (Front)	67.89
		Wrist (Front)	64.17					Forehead	68.70

Table 14
10-cross validation results of thermal satisfaction estimation accuracy.

#	Attribute	Accuracy (%)
1–1	Forehead	51.24
1–2	Wrist (Back)	50.69
1–3	Back	47.72
1–4	Waist	47.27
1–5	Arm	46.92
1–6	Wrist (Front)	45.23
1–7	Chest	44.36
1–8	Belly	43.54
1–9	Neck	43.22
1–10	Heart Rate	36.79
1–11	Gender	35.72
1–12	BMI	34.47
2–1	Forehead + Wrist (Back)	83.37
2–2	**Forehead + Wrist (Back) + Gender**	**88.52**
2–3	Forehead + Wrist (Back) + BMI	87.24
2–4	Forehead + Wrist (Back) + Heart rate	83.92
2–5	Forehead + Wrist (Back) + Back	91.36
2–6	Forehead + Wrist (Back) + Back + Gender	92.39
2–7	Forehead + Wrist (Back) + Back + Waist	93.26
2–8	Forehead + Wrist (Back) + Back + Waist + Gender	94.81
2–9	Forehead + Wrist (Back) + Back + Waist + Arm	94.81
2–10	Forehead + Wrist (Back) + Back + Waist + Arm + Gender	95.23
2–11	Forehead + Wrist (Back) + Back + Waist + Arm + Wrist (Front)	94.57

factors that may potentially affect the classification model. Also, this study sets an experiment thermal condition from 20 °C to 30 °C, but a broader or even more extreme thermal condition should be investigated to help understand the relationship between physiological responses and an individual's thermal satisfaction. Finally, subjective factors, such as personal thermal preference, aesthetical preference, and cultural background, could affect thermal satisfaction perceptions, so these factors should be considered in a future study as well.

Acknowledgement

This study was (partially) supported by the U.S. National Science Foundation Award #1707068 and the USC James H. Zumberge research and innovation fund. The authors would like to express gratitude to the USC students who volunteered for the experiments and their technical support with the experiments and data acquisition. The project was performed within the framework of the International Energy Agency Energy in Buildings and Communities programme (IEA-EBC) Annex 69 ″Strategy and Practice of Adaptive Thermal Comfort in Low Energy Buildings”.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2019.01.007.

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